AUTOMATIC MACHINERY FAULT DETECTION AND DIAGNOSIS USING FUZZY LOGIC

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Abstract: Machine condition monitoring incorporates a number of machinery fault diagnosis techniques. Many of these machinery fault diagnostic techniques involve automatic signal classification. In this paper Fuzzy logic techniques have been applied to classify frequency spectra representing various bearing faults. The frequency spectra have been processed by four common Fuzzy set shapes: linear, triangular, S-curve and Pi curve. The application of basic Fuzzy logic techniques has allowed Fuzzy numbers to be generated which represent the similarity between two frequency spectra. Correct classification of six different bearing fault spectra was observed when the frequency spectra were represented by Pi curves. The degree of membership of each individual spectrum with respect to the other spectra, however, indicated a certain degree of overlapping. Further investigations must be conducted in order to optimise the ability to classify spectra with a certain degree of overlapping or masking.

Key Words: Fault detection, fault diagnosis, frequency spectra, Fuzzy logic, machinery faults, rolling element bearings.

INTRODUCTION: Unexpected failures of machinery and automated systems can be reduced by incorporating planned maintenance and condition monitoring strategies. Condition monitoring strategies involve detection, identification, prediction and correction of faults during the operation of a system [1]. However, identification of machinery faults can be difficult in systems with a high degree of complexity, hence introducing uncertainties in the area of fault diagnosis.

Recently there has been a significant amount of research effort put into developing and implementing useful automated machinery fault detection and diagnostic tools. Most of these tools have been based on various pattern recognition schemes, knowledge based systems (expert systems) or artificial neural network systems. The main thrust of the work has been towards developing systems that are not only objective in their treatment of data and presentation of results but also flexible, thereby being applicable in a wide range of situations.

Fuzzy logic has gained a wide acceptance in other fields as a useful tool for blending objectivity with flexibility, particularly in the area of process control. The work reported on in this paper involves the use of Fuzzy logic principles to categorise vibration signals and thereby provide a means of objectively detecting and diagnosing machinery faults.

Fuzzy logic is also proving itself to be a powerful tool in knowledge modeling [2]. Its ability to handle ambiguities makes it a useful tool, especially in the area of diagnostics. Its application as a diagnostic technique for machinery faults may prove to be advantageous to companies who operate complex automated machines. The realisation of Fuzzy logic as a useful diagnostic technique will require further research and development.

FUZZY LOGIC: Fuzzy logic provides a method of reducing and explaining system complexity [2]. It deals with system uncertainties and ambiguities. It mimics human reasoning and allows variables such as time, acceleration, force, distance, etc., to be represented with a certain degree of uncertainty. Fuzzy logic allows the membership of a variable within a group to be esstimated with a particular degree of uncertainty. Application of Fuzzy logic to machinery fault diagnosis should allow the membership of an unknown frequency spectra to be determined with respect to the known frequency spectra of particular faults.

Fuzzy logic represents system parameters as normalised values between zero and one. The uncertainties and ambiguities associated with a system parameter can then be quantified in terms more easily interpreted by humans. For example; Is the temperature of 75°C high or low? If we know that 100°C is definitely high and 60°C is definitely low, 75°C may be considered somewhat more low than high but still not low. Fuzzy logic allows us to quantify the grey area between high and low rather than simply considering every temperature below 80°C (the mid point) to be low and every temperature above 80°C as high. So called crisp boundaries are made Fuzzy but in a quantified manner. The actual degree of membership of a system parameter (temperature) in a particular group (low) is indicated by the values between zero and one inclusive [2]. A membership of zero means that the value does not belong to the set under consideration. A membership of one would mean full representation of the set under consideration. A membership somewhere between these two limits indicates the degree of membership. The manner in which values are assigned membership is not fixed and may be established according to the preference of the person conducting the investigation.

Fuzzy sets can be represented by various shapes. They are commonly represented by S-curves, Pi curves, triangular curves and linear curves. The choice of the shape of the Fuzzy set depends on the best way to represent the data. The degree of membership is indicated on the vertical axis. In general, the membership starts at zero (no membership) and continues to one (complete membership). The domain of a set is indicated along the horizontal axis. The fuzzy set shape defines the relationship between the domain and the membership values of a set.

The S-Curve moves from no membership at its extreme left-hand side to complete membership at its extreme right-hand side. The inflection point of the S-Curve is at the 0.5 membership point. The S-curve can also represent declining membership. It is defined by three parameters; its zero membership value (α), its complete membership value (γ) and its inflection point (β). (See Figure 1.) The domain values of an S-Curve can be determined from the following relationships [2].

$$S(x;\alpha,\beta,\gamma) = \begin{cases} 0 & \rightarrow x <= \alpha \\ 2((x-\alpha)/(\gamma-\alpha))^2 & \rightarrow \alpha <= x <= \beta \\ 1-2((x-\gamma)/(\gamma-\alpha))^2 & \rightarrow \beta <= x <= \gamma \\ 1 & \rightarrow x >= \gamma \end{cases}$$

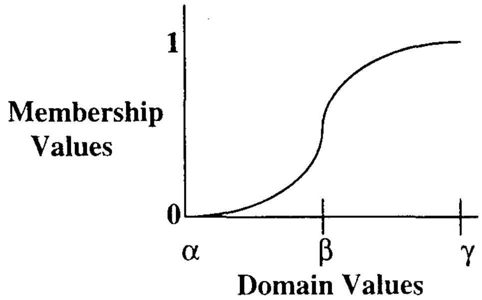

Figure 1. S-Curve

Pi curves are the preferred and default method of presenting Fuzzy numbers where membership values have lower and upper bounds [2]. The Pi curve represents full membership at its central value. A smooth descending gradient is then observed on either side of the central value where the membership approaches zero along the domain. The parameters of the Pi curve are; the central value (γ) and the width of half of the Pi curve (β). (See Figure 2.)

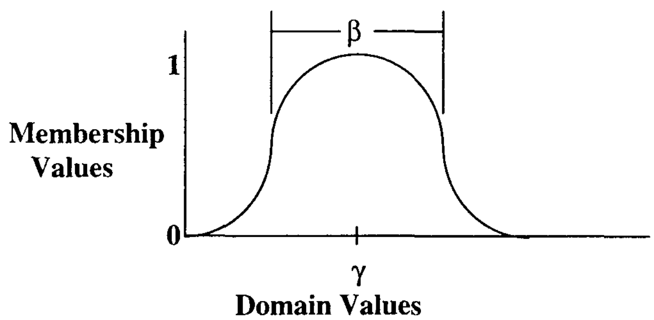

Figure 2. Pi Curve

The domain values of the Pi curve can be determined from the following relationships [2] where the Pi Curve is made up of ascending and descending S-Curves.

$$\mathbf{Pi}\ (x; \beta, \gamma) = \begin{cases} S(x; \gamma - \beta, \gamma - \beta/2, \gamma) & \rightarrow x <= \gamma \\ 1-S(x; \gamma, \gamma+\beta/2, \gamma+\beta) & \rightarrow x > \gamma \end{cases}$$

The linear Fuzzy set is the simplest Fuzzy set shape being basically a straight line. For an increasing linear Fuzzy set, no membership begins at the extreme left hand side. The line then increases linearly to the position where it represents complete membership on the right hand side. (See Figure 3.)

Fuzzy sets represented by triangular curves are similar to the Fuzzy sets represented by the Pi curve. The apex of the triangle is the central value and represents complete membership. The left and right edges of the triangle represent membership that tends toward non membership in the set. (See Figure 4.)

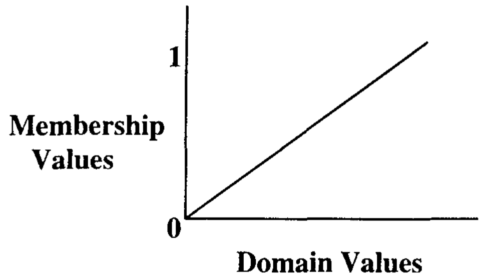

Figure 3. Linear Curve

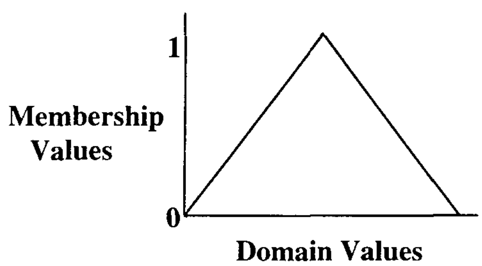

Figure 4. Triangular Curve

FUZZY SET OPERATORS: The main difference between Boolean logic and Fuzzy logic is that Boolean logic only has two states, one and zero. Fuzzy logic deals with uncertainties and hence, considers all values between zero and one. However, like conventional sets there are specifically defined operation for combining and modifying Fuzzy sets. These basic operations provide fundamental tools for Fuzzy logic. The basic Fuzzy logic operations are shown below.

Intersection: $A \cap B = \min(\mu_A[x], \mu_B[y])$
Union: $A \cup B = \max(\mu_A[x], \mu_B[y])$
Complement: $A = 1 - \mu_A[x]$

Above, **A** and **B** are sets of Fuzzy numbers and μ_A and μ_B are the individual Fuzzy membership values. The intersection of two Fuzzy sets involves taking the smallest membership value of the two Fuzzy sets. The union of two Fuzzy sets involves taking the largest membership value of the two Fuzzy sets. The complement of a Fuzzy set is determined by inverting the Fuzzy set shape at each point. For example, the compliment of an increasing linear Fuzzy set is a decreasing linear Fuzzy set [2]

FUSION FRAME WORK: An individual frequency spectrum can be identified with a class of spectra with similar characteristics. To obtain a final membership value of a sample of a particular class, Fuzzy logic operators can be used. First the union operator is used to combine all the available information about the different spectral features. For example, if frequency measurements were made for a particular fault at different time intervals, all the magnitude values taken at 50 Hz at the different time intervals would be combined. This procedure has also been found to be useful when the aim is to maximise all the information of the same feature coming from different sensors [3]. To finally establish the overall membership value of the spectra requires a more selective process. To narrow the selection of membership values obtained from the union operation, the intersection operation is used to obtain the final membership value of a particular class of spectra. The intersection operation makes establishing the final membership value of a particular class a more selective process, if there are a number of existing classes [3].

METHODOLOGY: The aim of this work was to investigate the use of basic Fuzzy logic concept for possible application as a machinery fault diagnostic tool. This diagnostic technique will be capable of automatic and objective machinery fault classification.

The data used in this research were frequency spectra obtained from a test rig used to conduct low speed rolling element bearing tests [4][5]. The frequency spectra obtained were representative of different bearing conditions. These bearing conditions were; Fault 1 - Inner race fault, Fault 2 - No fault, Fault 3 - Outer race fault, Fault 4 - Combination of outer race and rolling element faults, Fault 5 - Combination of outer, inner and rolling element faults, Fault 6 - Rolling element fault. The Pi curve, linear curve, S-curve and the triangular curve were used to represent the frequency spectra of the various bearing conditions. The main purpose of the investigation was to determine which Fuzzy set shape best represents the frequency spectra of the various bearing faults and how well the technique classified faults.

Programs coded in C were written to allow the various bearing fault conditions to be classified with respect to each other. The C programs implemented basic Fuzzy logic data fusion techniques with the corresponding Fuzzy shape to classify the various bearing conditions.

The way this investigation was approached was initiall to investigate each of the frequency spectra of the bearing conditions. The purpose of investigating each of the frequency responses was to determine the characteristic acceleration ranges of each of the bearing conditions. This would establish the ranges of each bearing condition when represented in a Fuzzy set of a particular shape. It was observed that when the frequency spectra were super imposed onto each other, there was a certain degree of overlapping. For this reason, the Fuzzy set shapes also displayed a certain degree of overlapping.

RESULTS: The programs written read in all the frequency spectral responses of a particular bearing condition to act as a data bank. One of the known frequency spectrum corresponding to a particular bearing condition was then input into the program. This spectrum was then considered as an unknown spectrum. If the spectrum corresponds to a particular bearing condition, its membership value will be high, indicating membership to that particular fault. If the unknown signal does not correspond to a particular fault condition it will have a lower membership value, indicating only partial or non-membership.

The tables given below are square matrices containing the various bearing conditions investigated. Only results from trials using the triangular and Pi curves are reported here. Linear and S-curves are not appropriate for the type of data representation used for the frequency spectra under consideration. Table 1 shows the results of the triangular curve classification trial and Table 2 shows the results of the Pi curve classification trial.

Table 1: Triangular Results

FAULTS:	1.	2.	3.	4.	5.	6.
1	**1.00**	0.85	0.78	1.00	1.00	0.65
2.	1.00	**0.99**	1.00	1.00	1.00	1.00
3.	0.82	0.77	**0.98**	0.00	0.00	0.57
4.	0.54	0.00	0.42	**0.66**	0.00	0.35
5.	0.00	0.00	0.00	0.00	**1.00**	0.00
6.	0.67	0.82	0.79	0.00	1.00	**0.84**

Table 2 : Pi Curve Results

FAULTS:	1.	2.	3.	4.	5.	6.
1.	**0.99**	0.96	0.98	0.85	0.00	0.96
2.	0.95	**0.98**	0.97	0.00	0.00	0.95
3.	0.97	0.95	**0.99**	0.94	0.00	0.98
4.	0.89	0.00	0.92	**0.98**	0.59	0.63
5.	0.00	0.00	0.00	0.03	**1.00**	0.00
6.	0.97	0.98	0.98	0.85	0.00	**0.99**

DISCUSSION: Linear curves, triangular curves, S-curves and Pi curves are the common set shapes used to represent data in Fuzzy logic. It was possible to code the various curves in the programming language of C to obtain membership values. A Fuzzy fusion framework based on basic Fuzzy logic operations was then used to obtain the final membership value of the unknown frequency spectral response data with respect to the known frequency response values stored in the program's data bank.

Tables 1 and 2 represent square fault matrices with the six known faults being compared to six known fault classes in a blind test. The six known fault classes are in the vertical columns and are actually groups of 15 sample spectra representing the different faults placed in the program's data bank. Six representative faults across the top row were considered to be unknown and were inputs to the programs of the various Fuzzy shapes. The order of the faults was the same for both the vertical column and the top horizontal row. For any particular Fuzzy set shape the results should show highest membership values in the diagonal of the table. This would indicate that the frequency spectra data input into the program displayed a high degree of membership to the corresponding known fault class.

The Fuzzy set shape which produced the most desirable results was the Pi curve. The results in Table 2 show membership values that were highest along the diagonal. This indicates that the corresponding faults had the highest degree of membership or can be considered most similar. In many cases there are significant differences between the various trial classifications. In some cases the value in the diagonal is much higher than the other numbers, in other cases the value is only slightly higher. This is to be expected as some of the frequency spectra are in fact more similar than are others.

Use of the triangular curve for Fuzzy classification trials (results shown in Table 1) resulted in promising classification results but also some errors. These errors occurred where there is an obvious similarity between the frequency spectra being compared. Some modifications to the data fusion method employed may provide grester numerical distinction between similar spectra. Perhaps some combination of Fuzzy logic set operations and classical statistical analysis would improve the results.

CONCLUDING COMMENTS: This work has investigated the use of basic Fuzzy logic techniques as a machinery fault diagnostic technique. The work conducted has displayed the potential of basic Fuzzy logic to classify frequency spectra according to the likely fault condition which they represent. However, further investigation must be conducted to optimise its ability to classify spectra when overlapping or masking exists. Its ability to classify and identify machinery faults shows considerable potential. With further research and development as a diagnostic tool, Fuzzy logic may have an important role to play in machine condition monitoring.

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